

# An Numerical Approach to Robust Partial Quadratic Eigenvalue Assignment in Second-Order Control Systems

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**In memory of Professor Gene Golub**

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## Motivation

## Active Vibration Control

Applications

Main Goals

## Quadratic Eigenvalue Assignment Problem

Modelling

Partial Quadratic Eigenvalue Assignment Problem–PQEAP

## Minimization Norm and Robust PQEAP

Difficulties

## Existing Methods

Feedback Norm Minimization Problem

Robust PQEAP

## Our Work

Parametric Solutions to PQEAP

Robust PQEAP

Numerical Results

Figure: Wobbling of the Millennium Footbridge Over the River Thames



# Instability of Vibration Structures

- Resonance: The structure is excited by external forces whose frequencies are close to its natural frequencies. The vibrations are amplified and the system becomes unstable.
- Vibration control of structures (e.g. bridges, highways, and aircrafts) are essential to achieve optimal design with desirable performance.
- Traditional Method: Passive damping treatment. Reliable, robust, and without significantly altering the structural mass and stiffness but unadjustable.
- More Popular Method: Active Vibration Control. Adjustable and significant damping.

# Applications of Active Vibration Control

- Large flexible space structure control;
- Earthquake engineering;
- Control of flexible multibody systems;
- Controller design for damped gyroscopic systems;
- Vibration in structural dynamics.

# Main Goals of Active Vibration Control

- Determine a state feedback controller to reduce vibrations (e.g. eliminate the resonant frequencies);
- Keep crucial system properties unchanged.

## Modelling:

$$M\ddot{\mathbf{x}}(t) + D\dot{\mathbf{x}}(t) + K\mathbf{x}(t) = B\mathbf{u}(t).$$

- The dynamical characteristics of a structure are governed by the natural frequencies and mode shapes, i.e., the eigenvalues and eigenvectors of the quadratic eigenvalue problem:

$$P(\lambda)\mathbf{x} := (\lambda^2 M + \lambda C + K)\mathbf{x} = \mathbf{0}.$$

- The control force

$$\mathbf{u}(t) = F_1^T \dot{\mathbf{x}} + F_2^T \mathbf{x}(t)$$

leads to the close-loop pencil

$$P_c(\lambda) := \lambda^2 M + \lambda(D - BF_1^T) + (K - BF_2^T) = \mathbf{0}.$$

## Partial Quadratic Eigenvalue Assignment Problem:

- Find the feedback matrices  $F_1$  and  $F_2$  such that the few unwanted eigenvalues

$$\lambda_1, \dots, \lambda_p \ (p \ll 2n)$$

are reassigned to the desired ones:

$$\mu_1, \dots, \mu_p.$$

- The other  $2n - p$  eigenvalues and eigenvectors of the open-loop pencil  $P(\lambda)$  are preserved (*no spill-over phenomenon*).



## Remarks

- Retaining the “acceptable” (e.g. no-resonant) eigenvalues and eigenvectors can ensure that there is no spurious modes will be introduced into the frequency range of interests;
- One may transform the second-order model to the first-order control system

$$\dot{\mathbf{z}}(t) = \hat{\mathbf{A}}\mathbf{z}(t) + \hat{\mathbf{B}}\mathbf{u}(t),$$

where

$$\hat{\mathbf{A}} = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}D \end{bmatrix}, \quad \hat{\mathbf{B}} = \begin{bmatrix} 0 \\ M^{-1}B \end{bmatrix}, \quad \mathbf{z}(t) = \begin{bmatrix} \mathbf{x}(t) \\ \dot{\mathbf{x}}(t) \end{bmatrix}.$$

## Remarks

- The PQEAP is converted the pole assignment problem for the first-order control systems where many numerical methods are available, see Chu'07;
- Computational Drawbacks:
  - ▶ Increase in dimensionality from  $n$  to  $2n$ ;
  - ▶ Inversion of a possibly ill-conditioned mass  $M$ ;
  - ▶ loss of exploitable structures such as the symmetry, definiteness, sparsity and bandedness.

Therefore, the PQEAP is substantially different from the first-order pole assignment problem.

# Minimization Norm and Robust PQEAP

From a practical point of view, it is desirable to determine feedback matrices  $F_1$  and  $F_2$  such that.

- ▶ The feedback norm is minimized. small feedback gains lead to smaller control signals, and thus to less energy consumption. Also, small gains reduce noise amplification.
- ▶ The sensitivity of the close-loop eigenvalues is minimized. This is *robust* PQEAP.

## Challenges:

- ▶ The problem must be considered in the quadratic setting without the transformation to the first order state space forms.
- ▶ Only the few reassigned open-loop eigenvalues and the associated eigenvectors are available.
- ▶ No spill-over phenomenon should be guaranteed.
- ▶ No model reduction is allowed.
- ▶ The gradient formulas of the objective function should be in terms of the few known eigenvalues and eigenvectors only.

# Notations

- ▶  $\Lambda_1 = \text{diag}(\lambda_1, \dots, \lambda_p)$ : The eigenvalues to be reassigned;
- ▶  $X_1 = [\mathbf{x}_1, \dots, \mathbf{x}_p]$ : The matrix of the eigenvectors corresponding to the eigenvalues  $\lambda_1, \dots, \lambda_p$ ;
- ▶  $\Lambda'_1 = \text{diag}(\mu_1, \dots, \mu_p)$ : The eigenvalues to assign;
- ▶  $\Lambda_2 = \text{diag}(\lambda_{p+1}, \dots, \lambda_{2n})$ : The  $2n - p$  open-loop eigenvalues (unavailable);
- ▶  $X_2 = [\mathbf{x}_{p+1}, \dots, \mathbf{x}_{2n}]$ : The matrix of the eigenvectors corresponding to the eigenvalues  $\lambda_{p+1}, \dots, \lambda_{2n}$  (unavailable);
- ▶  $Y_1$ : Close-loop eigenvectors corresponding to the eigenvalues  $\mu_1, \dots, \mu_p$ .

# Assumptions

- ▶  $M, D, K$  real symmetric with  $M > 0$ .
- ▶ Partial Controllability of the model  $(P(\lambda), B)$

$$\text{rank}(\lambda_i^2 M + \lambda_i D + K, B) = n \text{ for } i = 1, \dots, p.$$

- ▶ Sets of eigenvalues are closed under complex conjugation.
- ▶  $0 \notin \{\lambda_1, \dots, \lambda_p\}$ .

## Parametric Expressions for the feedback Matrices

**(Theorem:Brahma and Datta'07)** The feedback matrices  $F_1$  and  $F_2$  are determined by

$$\begin{cases} F_1 &= MX_1 \Lambda_1 \Phi^T \\ F_2 &= -KX_1 \Phi^T \end{cases}$$

where  $\Phi$  satisfies

$$\Phi Z = \Gamma \text{ } (\Gamma \text{ arbitrary})$$

with  $Z$  being the unique solution of the Sylvester equation:

$$\Lambda_1 Z - Z \Lambda_1' = -\Lambda_1 X_1^T B \Gamma.$$

# Feedback Norm Minimization Problem

Let

$$S := [F_2^T, F_1^T]$$

$$\min \quad \Pi := \frac{1}{2} \|S\|_F^2 = \frac{1}{2} (\|F_1\|_F^2 + \|F_2\|_F^2)$$

## • Theorem for Gradient Formula (Brahma and Datta'07):

- ▶ Let  $C := [-X_1^T K, \Lambda_1 X_1^T M]$ . Then

$$S = \Gamma Z^{-1} C$$

- ▶ Let  $U$  be the solution to the Sylvester equation

$$\Lambda_1' U - U \Lambda_1 = -Z^{-1} C S^H \Phi.$$

Then,

$$\nabla_{\Gamma}(\Pi) = 1/2 [Z^{-1} C S^H - U \Lambda_1 X_1^T B]^T.$$



# Robust PQEAP

The close-loop eigenvectors

$$Y = \begin{bmatrix} Y_1 & X_2 \\ Y_1 \Lambda_1' & X_2 \Lambda_2 \end{bmatrix}$$

where  $Y_1 = [\mathbf{y}_1, \dots, \mathbf{y}_p]$  with  $\mathbf{y}_k$  satisfying  $(\mu_k^2 M + \mu_k D + K)\mathbf{y}_k = B\gamma_k$ .

$$\min J := \|(I - Y^H Y)^2\|_F^2$$

## • Theorem for Gradient Formula (Brahma and Datta'07):

►  $J = \|(I - Y^H Y)^2\|_F^2 = \|Z_1\|_F^2 + \|Z_2\|_F^2 := J_1 + J_2$ , where

$$Z_1 = I_p - Y_1^H Y_1 - \bar{\Lambda}_1' Y_1^H Y_1 \bar{\Lambda}_1, \quad Z_2 = I_{2n-p} - X_2^H X_2 - \bar{\Lambda}_2 X_2^H X_2 \bar{\Lambda}_2.$$

►

$$\nabla_{\Gamma}(J) = \nabla_{\Gamma}(J_1) \quad (\nabla_{\Gamma}(J_2) = 0),$$

where  $\nabla_{\Gamma}(J_1)$  is given in terms of  $Y_1$ ,  $X_1$ , and  $\Lambda_1$  only.

# Parametric Solutions to PQEAP

**Attn:** The assumption that  $0 \notin \{\lambda_1, \dots, \lambda_p\}$  is canceled.

- The feedback matrices  $F_1$  and  $F_2$  are given by

$$\begin{cases} F_1 &= MX_1 \Phi^T \\ F_2 &= (MX_1 \Lambda_1 + DX_1) \Phi^T \end{cases}$$

where  $\Phi$  satisfies

$$\Phi Z = \Gamma \quad (\Gamma \text{ arbitrary})$$

with  $Z$  being the unique solution of the Sylvester equation:

$$\Lambda_1 Z - Z \Lambda_1' = -X_1^T B \Gamma.$$

# Robust PQEAP

The close-loop eigenvectors

$$Y = \begin{bmatrix} Y_1 & X_2 \\ Y_1 \Lambda_1' & X_2 \Lambda_2 \end{bmatrix}$$

where  $Y_1 = [\mathbf{y}_1, \dots, \mathbf{y}_p]$  with  $\mathbf{y}_k$  satisfying  $(\mu_k^2 M + \mu_k D + K)\mathbf{y}_k = B\gamma_k$ .

$$\min J := \frac{1}{2}(1 - \alpha)(\|F_1\|_F^2 + \|F_2\|_F^2) + \frac{1}{2}\alpha(\|Y\|_F^2 + \|Y^{-1}\|_F^2),$$

where  $0 \leq \alpha \leq 1$ .

## Remarks

- Reduction of  $J$ :

$$\begin{aligned}
 J &= \frac{1}{2}\alpha(\|Y_1\|_F^2 + \|Y_1\Lambda_1'\|_F^2) + \frac{1}{2}\alpha\|Y^{-1}\|_F^2 \\
 &+ \frac{1}{2}(1-\alpha)(\|F_1\|_F^2 + \|F_2\|_F^2) \\
 &+ \frac{1}{2}\alpha(\|X_2\|_F^2 + \|X_2\Lambda_2\|_F^2) \\
 &:= J_1 + J_2 + J_3.
 \end{aligned}$$

- Challenges:

- ▶ Could we get an explicit expression for  $Y^{-1}$ ?
- ▶ How to find the gradient formula for the above cost function without knowing  $\Lambda_2$  and  $X_2$ ?
- If the formula is found, then an optimization technique such as Broyden-Fletcher-Goldfrab-Shanon (BFGS) method can be employed.

# Expression of $Y^{-1}$

• **Theorem:** Let

$$\begin{cases} C &:= [\Lambda_1 X_1^T M + X_1^T D, X_1^T M], \\ \tilde{Y}_1 &:= [Y_1^T, \Lambda_1' Y_1^T]^T, \\ \tilde{X}_2 &:= [X_2^T, \Lambda_2 X_2^T]^T. \end{cases}$$

Then

$$Y^{-1} = \begin{bmatrix} Z^{-1}C \\ \tilde{X}_2^+(I - \tilde{Y}_1 Z^{-1}C) \end{bmatrix} := \begin{bmatrix} W_1 \\ W_2 \end{bmatrix}.$$

# Comments

It follows that

$$\|W_2\|_F \leq \|\tilde{X}_2^+\|_2 \|(I - \tilde{Y}_1 W_1)\|_F = 1/\sigma_{\min}(\tilde{X}_2) \|I - \tilde{Y}_1 W_1\|_F.$$

By the assumption that  $\tilde{X}_2$  has linearly independent columns, one may expect that  $\sigma_{\min}(\tilde{X}_2)$  is not too small. Suppose that  $\beta$  is *a-priori* estimate of  $1/\sigma_{\min}^2(\tilde{X}_2)$ . Therefore, we shall minimize

$$\begin{aligned} J &= \frac{1}{2}\alpha(\|Y_1\|_F^2 + \|Y_1\Lambda_1'\|_F^2 + \|W_1\|_F^2 + \beta\|I - \tilde{Y}_1 W_1\|_F^2) \\ &+ \frac{1}{2}(1 - \alpha)(\|F_1\|_F^2 + \|F_2\|_F^2) \\ &+ \frac{1}{2}\alpha(\|X_2\|_F^2 + \|X_2\Lambda_2\|_F^2) \\ &:= J_1 + J_2 + J_3 \quad (\text{for simplicity}). \end{aligned}$$

## Gradient Formula

- **Theorem:** Let  $U$ ,  $U_1$ ,  $U_2$ ,  $\Upsilon$ ,  $V$ ,  $V_1$ , and  $V_2$ , respectively, satisfy the following equations

$$\begin{cases} MU\Lambda_1'^2 + DU\Lambda_1' + KU = [(I + \Lambda_1'\bar{\Lambda}_1')Y_1^H]^T, \\ MU_1\Lambda_1'^2 + DU_1\Lambda_1' + KU_1 = [W_1W_{11}^H]^T, \\ MU_2\Lambda_1'^2 + DU_2\Lambda_1' + KU_2 = [\Lambda_1'W_1W_{21}^H]^T \end{cases}$$

and

$$\begin{cases} \Lambda_1'\Upsilon - \Upsilon\Lambda_1 = -Z^{-1}CS^H\Phi \\ \Lambda_1'V - V\Lambda_1 = -W_1W_1^HZ^{-1}, \\ \Lambda_1'V_1 - V_1\Lambda_1 = -W_1W_{11}^HY_1Z^{-1}, \\ \Lambda_1'V_2 - V_2\Lambda_1 = -W_1W_{21}^HY_1\Lambda_1'Z^{-1}, \end{cases}$$

## Gradient Formula

where

$$W_{11} = E_1 - Y_1 W_1 \quad \text{and} \quad W_{21} = E_2 - Y_1 \Lambda_1' W_1$$

with  $E_1 := [I_n, 0] \in \mathbb{R}^{n \times 2n}$  and  $E_2 := [0, I_n] \in \mathbb{R}^{n \times 2n}$ . Then,

$$\nabla_{\Gamma} J = \alpha \nabla_{\Gamma} J_1 + (1 - \alpha) \nabla_{\Gamma} J_2,$$

where

$$\begin{aligned} \nabla_{\Gamma} J_1 &= \frac{1}{2} [U^T B + V X_1^T B]^T \\ &\quad - \frac{1}{2} \beta [(U_1 + U_2)^T B + (V_1 + V_2) X_1^T B]^T, \\ \nabla_{\Gamma} J_2 &= \frac{1}{2} [Z^{-1} C S^H - \gamma X_1^T B]^T. \end{aligned}$$



# Numerical Results

## Problem 1:

$$\bullet M = \begin{bmatrix} 1.0000 & 0.0167 & -0.1428 & 0.1971 \\ 0.0167 & 1.0000 & -0.0524 & 0.5457 \\ -0.1428 & -0.0524 & 1.0000 & -0.2326 \\ 0.1971 & 0.5457 & -0.2326 & 1.0000 \end{bmatrix}, D = \begin{bmatrix} 1.0000 & -0.0527 & -0.2816 & -0.3331 \\ -0.0527 & 1.0000 & 0.3098 & -0.3367 \\ -0.2816 & 0.3098 & 1.0000 & 0.3715 \\ -0.3331 & -0.3367 & 0.3715 & 1.0000 \end{bmatrix}$$

$$K = \begin{bmatrix} 0.7330 & 0.4380 & -0.0860 & 0.6015 \\ 0.4380 & 0.3108 & 0.1600 & 0.1961 \\ -0.0860 & 0.1600 & 0.9198 & -0.7733 \\ 0.6015 & 0.1961 & -0.7733 & 1.0364 \end{bmatrix}, B = \begin{bmatrix} 0.1987 & 0.0153 \\ 0.6038 & 0.7468 \\ 0.2722 & 0.4451 \\ 0.1988 & 0.9318 \end{bmatrix}$$

- The open-loop eigenvalues are:  
 $\{-3.4209, -0.1943 \pm 1.0642i, 0.0000, -0.5474 \pm 0.8820i, -1.0777, 0.0000\}$ . The eigenvalues  $\{0.0000, 0.0000\}$  were reassigned to  $\{-0.3 \pm 1.5i\}$ , the other eigenvalues were retained.

## Numerical Results

Problem 2 (Nichols & Kautsky'01):

•

$$M = 10I_3, \quad D = 0, \quad K = \begin{bmatrix} 40 & -40 & 0 \\ -40 & 80 & -40 \\ 0 & -40 & 80 \end{bmatrix}, \quad B = \begin{bmatrix} 1 & 2 \\ 3 & 2 \\ 3 & 4 \end{bmatrix}.$$

- The open-loop eigenvalues are:  $\{\pm 3.6039i, \pm 2.4940i, \pm 0.8901i\}$ . The first two eigenvalues  $\{\pm 3.6039i\}$  were reassigned to  $\{-1, -2\}$ , the other eigenvalues were preserved.

## Numerical Results

Problem 3 (Tisseur & Meerbergen'01):

•

$$M = I_n, D = \tau \text{tridiag}(-1, 3, -1), K = \kappa \text{tridiag}(-1, 3, -1), B = \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \\ 0 & -1 \end{bmatrix}$$

- $n = 50$ ,  $\tau = 3$ , and  $\kappa = 5$ .
- The first six open-loop complex eigenvalues  $\{-3.3306 \pm 0.0947i, -3.1628 \pm 0.7344i, -3.0000 \pm 1.0000i\}$  were reassigned to  $\{-3.5 \pm 0.0947i, -3.5 \pm 0.7344i, -3.5 \pm 1.0000i\}$ . The other 94 eigenpairs are kept unchanged.

**Table:** Numerical results for Problems 1–3 (“e5” means “ $\times 10^5$ ”)

	Mini-N	$\beta = 1$		$\beta = 10^2$		$\beta = 10^4$	
	$\alpha = 0$	$\alpha = 1$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 0.5$	$\alpha = 1$	$\alpha = 0.5$
$\ F_1\ _F$	20.09	12.88	12.38	21.78	21.12	18.96	21.77
$\ F_2\ _F$	23.40	12.19	12.73	51.05	49.00	40.92	51.04
$\kappa_2(Y)$	6.8e12	22.03	24.17	162.81	158.34	569.64	162.49 <sup>P1</sup>
$\ F_1\ _F$	19.36	26.58	21.31	26.87	30.11	26.88	26.93
$\ F_2\ _F$	70.89	99.68	72.23	99.52	95.67	99.52	99.47
$\kappa_2(Y)$	4.86e3	10.19	177.05	10.22	11.41	10.22	10.22 <sup>P2</sup>
$\ F_1\ _F$	5.24	18.23	23.41	273.42	584.51	28.94	28.94
$\ F_2\ _F$	18.22	74.04	92.41	$1.0 \cdot 10^3$	$2.3 \cdot 10^3$	122.13	122.13
$\kappa_2(Y)$	2.2e9	2.9e5	4.2e5	1.0e7	1.8e7	7.6e5	7.6e5 <sup>P3</sup>

**Table:** Numerical results for Problems 2 and 3 ( $RE. = 100 \times (IV. - FV.) / IV.$ )

	Brahma-Datta's Robust Mehtod			Our method with $\alpha = 1, \beta = 10^2$		
	$\ F_1\ _F$	$\ F_2\ _F$	$\kappa_2(Y)$	$\ F_1\ _F$	$\ F_2\ _F$	$\kappa_2(Y)$
IV.	74.98	130.71	$6.98 \times 10^3$	74.98	130.71	$6.98 \times 10^3$
FV.	59.44	161.54	232.99	26.87	99.52	10.22
RE.	20.72	-23.58	96.66	64.16	23.86	$99.85^{P2}$
IV.	5.1067	17.83	$8.37 \times 10^3$	5.1067	17.83	$8.37 \times 10^3$
FV.	6.6371	21.84	$3.28 \times 10^3$	5.1281	17.80	$1.57 \times 10^3$
RE.	-29.97	-22.46	60.79	-0.42	0.20	$81.30^{P3}$

# Thank You!